Using an Autonomous Service Robot for Detection of Floor Level Obstacles and its Influence to the Gait

A Futher Step to an Automated Housing Enabling Assessment

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***Abstract*—Depending on the aging society, new care concepts for older people are needed, especially the preservation of the personal mobility should be in focus. A solution could be the use of Information and Communication Technology (ICT) based solutions. A key role to preserve the autonomy and social interaction of older persons is their mobility. The prevention of fall events is a goal for the Housing Enabling (HE) Assessments by adaption of room, e.g., by detecting and removing tripping hazards. It was pointed out, that an automated HE Assessment executed by an autonomous service robot could reach a better quality and a higher acceptance. In this paper, we present the first try to detect relevant unevenness of the floor in home environments with an autonomous service robot and the resulting problems. For the gait analysis, we used a Microsoft® Kinect and for measurement of the unevenness of the floor we used the Primesense Carmine 1.08 depth sensor. First results explain which kind of influence the environment to gait parameters has (gait speed, step / stride length and the variation) and that it is mandatory to factor the conditions of the floor into an in-home gait analysis.**

Keywords-Mobile robot; gait analysis; floor level; Housing Enabling

I. INTRODUCTION

Industrial countries have to cope with different problems caused by the demographic change [1]. A possible way to cope with these upcoming problems is the use of ICT in the Ambient Assisted Living (AAL) area. There are two approaches to bring the technology to the homes of elderly people. The first and older solutions are smart homes [8], where the whole technology is integrated in the flat. The second is the field of autonomous service robots. In this case the sensors, actuators and the computational unit are mounted on a mobile base. The simplest representatives are household robots like autonomous vacuum cleaners, which raise the acceptance of users. Advanced Systems could support the caretakers and assist elderly in an independent lifestyle and preserve their indoor mobility up to a high age [2][4]. One advantage of service robots is reduced costs compared to smart homes. They need only few sensors to generate a good coverage which depends on their mobility, so they can bring them in the area of interest [3]. We will use the mobility of these platforms to realize a new approach of the HE assessment. A first step is the evaluation of the flat, for example the examination of the floor to detect stumbling risks. The rest of this paper is organized as follows. Section II gives a short motivation about the topic, followed by the state of the art and the current limitation of it (Section III). In Section IV, we present our first approach to measure the unevenness of the floor and the results in Section V. The conclusions and further steps close the article (Section VI).

II. MEDICAL MOTIVATION

Fall-related costs are one of the major factors influencing the proportionally higher costs to the health care system caused by elderly people. From a clinical perspective long-term monitoring of changes in mobility has a high potential for early diagnosis of various diseases and for assessment of fall risk [4]. As important as the age and potential diseases of the patient [5][6] are the condition of the floor for the self-selected gait velocity and in general for the risk of stumbling. Especially in an unsupervised environment the additional information about the quality of the floor could increase the precision of the gait analysis [9][10] and a precise gait analysis could be very helpful for the HE assessment to estimate the personal factor. In our approach, we try to realize both, good results for the HE assessment and also additional information for a gait analysis to increase their precision.

III. STATE OF THE ART

A. Trend Analysis of mobility in Domestic Environments

There are different approaches for gait analysis, so is it possible to upgrade a home with various sensors, especially from the home automation or security domain to a (health) smart home [13]. Most systems are used for a trend analysis and only some approaches use ambient sensors for detailed gait analysis. Various groups use home automation technologies like motion sensors, light barriers or reed contacts placed in door frames or on the ceiling other than Cameron et al. [14], which use optical and ultrasonic sensors. These were placed on both sides above the door frames to determine the walking speed and direction of a person passing. Kaye et al. [15] presented a study based on sensors covering different rooms of a flat. Also, laser range scanners are used for Time Up and Go (TUG) assessment [16] or for detailed gait analysis [31]. Poland et al. [17] used a camera

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attached to the ceiling, recording a marked floor evenly divided into rectangles (virtual sensor). For persons within these, the approach ‘activates’ the virtual sensor in which they are currently located. Stone and Skubic [18] used the Kinect to analyse the gait in a home environment. Especially, the variation of different gait parameters like step length and self-selected gait speed over time was measured and identified as independent factors for the personal stumbling risk. Also, Gabel et al. [19] used the MS Kinect for a full body gait analysis which is capable for a precise in home gait analysis. A similar approach for a long time in house gait analysis by using the Kinect is published by Stone and Skubic [30].

B. Mobility Assessments Using Service Robotics

Service robots combine ideas of different fields of robotic research into one system to target at a specific application. Most available platforms are still in (advanced) research states. There are different fields of interest, e.g., acting autonomously in home environments [20], learning of environmental factors and user behaviour [21][29] and as well as robot designs itself [24]. Within our own work [23] we have recently presented a new approach to enhance mobile robot navigation in domestic environments by the use of mobility assessment data. The advantage of a mobile robot is that it can bring the needed sensor technology to the Optimal Observation sLots (OOL) for monitoring, as introduced in [24]. In the observation phase the robot stands at a safe place in the initial room of the flat and observes the human behaviour and environment. These data are used to compute new OOL, which fulfil different safety and quality criteria. After that phase the robot will travel to that OOL and measure different gait parameters by using the laser range scanner and the Kinect, which can be used in HE.

C. Housing Enabling

A quite popular assessment in the Scandinavian countries is the housing enabling assessment. It reduces the risk of fall in home environments and the near surrounding. The flats will correlate relating to the personal health status of the inhabitants [25] and the structure of the flat itself. This rating gives advice how to change the flat with its furniture etc. so that it is suitable for the resident. The housing enabling assessment is split into three parts. The first part is the descriptive part to collect some general information about the flat and the condition of the user. The second part is the evaluation of functional limitations and dependence on mobility aids. Detailed information about medical condition of the user is collected, e.g., severe loss of sight or limitation of stamina. The last part is based on different questionnaires, which are related to the flat and the surroundings. After completion of all questions, the score of the flat in relation to the actual health status of the user [27] could be computed [26]. The adaption of the flat is related to the rating [28] in order to reduce the risk of falling is also possible.

D. Determine the unevenness of the floor

There are several different building regulations [12], which identified different levels, which should not be exceed. These regulations are only obligatory for public buildings, but unevenness also influences the gait velocity [9]. To raise the validity of domestic gait analysis it is important to have detailed information about the floor. Udsatid et al. [29] used a mobile robot and a Kinect sensor to measure the ground and calculate a virtual ground plane. But, only for a background subtraction for a foot tracking algorithm, which was used by a side by side navigation algorithm. Currently, there are no mobile service robots to determine the unevenness of the floor.

E. Limitation of the State of the Art

As shown in section III-A, most of the systems use ambient sensors and do not observe the user continuously. This means, that only presence at specific known points is measured. The problem of this kind of monitoring is, that it can only be used for trend analysis instead of a detailed assessment to determine different mobility parameters of a person. For precise assessments of the mobility, laboratory equipment and a well-known surrounding are needed. On the one hand, the installation affords and costs are too high to install it in domestic homes, on the other hand homes are “floating”, this means that, e.g., the furniture changes over time. All of the automated gait analyses don’t respect the influence of the floor cover. Within the domain of health care and rehabilitation service robotics there are quite few systems commercially available. Further, there is no robotic system that is capable of doing HE assessments and tries to present advice to reduce the risk of falling. The current HE tests suffer from some drawbacks, e.g., the estimation of the personal disorders, the investigation and also the following adaption of the flat depends highly on the skill of the person executing the test. This could lead to different or insufficient results. Furthermore, this assessment is mostly not done as a continuously assessment, but rather as an event triggered assessment after accident. In summary, there is currently no system or approach available, that is capable of doing precise and continuous housing enabling assessments in domestic environments and using this additional information from to raise the precision of gait assessment results.

IV. APPROACH

A. Detection of Unevenness

Our own approach provided an automated and continuous detection of relevant unevenness/texture of the floor assembly, which will be used to rate the flat during the HE Assessment and to raise the quality of the gait analysis. To implement a stable algorithm in an unsupervised environment, we include at the start a self-calibration to calculate the ground level and the sensor orientation for a better error correction. This step is necessary, because it could happen that the orientation of the sensor changes a little between runs or the sensor underlies a drift over time. In this case a pre-calculated ground plain would lead to a wrong detection of relevant unevenness of the floor. In a first step we estimate the quality of the current depth image of the sensor, by calculating the Root-Mean-Square (RMS) deviation of each pixel.

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Figure 1. Left side: Depth values from the Sensor in grayscale (White near, dark grey far away) with a 10mm doorstep in a distance of 80cm, right side: Visualisation after ground subtraction and convert to a binary image of depth values with the RMS as threshold

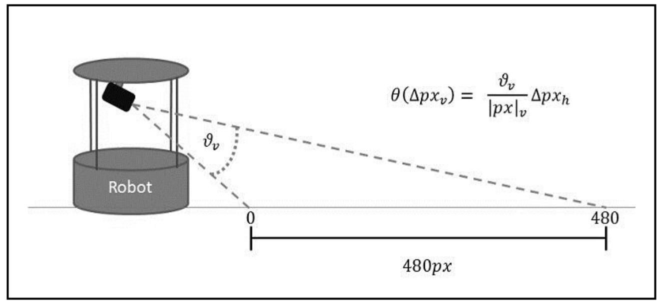

Figure 2. Schematic draw of the mobile service robot with the Primesense Sensor and the calculation of the vertical aperture angle between two points.

The median value of these results is used as a quality factor for the selection of depth points with a low noise. To calculate the virtual ground two points of the middle row and two of the middle column of the depth frame are selected which satisfy three criteria. The first is that both points have the lowest possible RMS (minimum below the quality factor otherwise use other column or row), the second is to maximize the distance between these points and the third criterion is that they don't belong to a known obstacle like walls. This information came from the navigation map of the mobile platform. In the following section we only look on the estimation of a vertical ground line, in fact the calculation of the horizontal ground line and therefore the ground plane is straight forward. After the selection of two vertical points we're able to calculate the first ground line and the vertical orientation of the sensor. Only five parameters are known, the two distance values of the two selected points and the pixel distance between both points. The vertical aperture angle of the Primesense Sensor [11] and the resolution of current depth frame are known. Figure 2 shows the aperture angle calculation of each pixel. Together with the pixel distance between the selected points we get the angle between it. For all Examples, we used a resolution of 640px times 480px, which is the highest possible depth resolution of the Primsense Carmine Sensor. Using the law of cosines, it's possible to estimate the missing parameters like the height of the sensor or the vertical angle. After the complete calculation all relevant values are known to estimate the vertical ground line. The next step is similar to the background subtraction. We use the ground line as a kind of background and calculate the difference to the current depth image. Figure 1 shows the normal depth image and a binary picture, which is generated by a root-mean-square deviation approach. If the difference is higher than the RMS, the pixel is set to 1, otherwise to 0. Now, it is easier to cluster this picture and find relevant trip hazards. Therefore many approaches are published, e.g., edge detection and many more. After we found interesting blobs (e.g. size or shape), we calculated the height of these obstacles from the depth picture and saved this information into the navigation map of the robot. After that we can use it during the scoring of the flat and to raise the precision of the gait analysis and the balance analysis on the different areas.

B. Calculate Balance Parameter

In our first approach, we use the Microsoft Kinect [31] to track the person because of the low price and the existing openNI skeleton tracking algorithm from ROS. The mobile platform does not move during the measurements, because of the specification from the openNI Algorithm. During the observation phase the timestamp, x-, y- and z- coordinates of the following skeleton joint point from the openNI tracker node will be saved:

- Foot and hip (each: left, right)
- Torso and Neck

In respect to the low processor capacity of the Turtlebot 2 netbook we used an offline approach. After the observation phase, different balance and gait analysis parameters are calculated. As a first validation the distances of the joint points are checked, whether they are between ranges of 0.80 – 3.00m, which is the effective distance of the Primesense sensor. After that, we calculate the gait speed, step and stride length and related to those values the stance and swing phase for each foot. First, we estimate the different phases from each foot during a measurement by using formula 1.

$$\lfloor x_i - x_{i+1} \rfloor_{i=0}^{n} = \begin{cases} \leq 0.02\,m, & stance\ phase \\ > 0.02m, & swing\ phase \end{cases} \quad (1)$$

This means that a foot needs a minimum acceleration of approx. 0,6m/s to mark as moving. This value reflected a compromise of literature values and a kind of error correction of the drift from skeleton tracking. After that the middle index of each phase for each foot was calculated, these are used to estimate the stride and step length. Also, the calculation of the gait speed used these indexes, by choosing the first and the last stand phase of each measurement and calculates the distance between these points. Now the corresponding timestamps are used to determine the elapsed time and by dividing the distance through the time we get the gait speed for each measurement. We used two facts to get a better reliable between measurements, the first is that the mobile robot stands on a defined OOL, so the global coordinates and the direction are nearly equal between the measurements; the second helpful point is that humans used more or less the same path between two points in the home environment. These points help to get a bigger and comparable data base from same OOL's

V. RESULTS

A. Detection of Unevenness

To test and verify our approach, we used the OFFIS IDE-AAL Lab, which provides a complete demo flat for first measurements in a realistic environment. As mobile platform a Turtlebot 2 (Kobuki) is used with Primesense Carmine 1.08 Sensor, which is mounted upside down below the third level of the platform and looks down to the ground with an angle of approx. 35 degrees at a height of approx. 34 cm. The resolution of the depth sensor is set to 640px times 480px and a frame rate of 30 Hz. The platform, the sensor and the fixing of both have not been changed during the measurements. To get comprehensive measuring results, we used the IDEAAL Lab and the normal office space to test our approach on different floor types. So we got results from two different carpets, laminate and PVC coating. The measurement in between two floors represents the change between coatings (laminate / carpet). To measure normalized height difference, 5 wooden footsteps layers are used. Each piece has a height of 5 mm, so that we're able to measure between uneven doorways (0mm) up to 25 mm. For each test set-up 30 single frames are saved and the mean values and the standard deviation for each pixel, to verify the precision of the sensor, are calculated. According to different buildings regulations [12], the requirement is to detect differences of a minimum of 4 mm between two surfaces. The measured minimal standard deviation is approx. 3.94 mm and the median value is 6.29 mm. This means that the precision of the Primesense Carmine 1.08 sensor is near to the required precision of 4mm. After this result we performed further tests to verify our first results. Therefore we made different measurements in the IDEAAL Lab and at the office with the wooden doorsteps. The proceeding for each measurement was the same, first we took 30 frames of the even surface, 30 frames with a 5 mm doorstep in a distance of 80 cm followed by 30 frames with 10 mm doorstep and so on until we reached the maximum of 25 mm. After that we reduced the distance to 40 cm and started over without any obstacles and then raised the doorsteps in 5 mm steps. After the measurement, we calculated the virtual ground plan and subtracted it from the different test images.

The result was unexpected; in the first approach, we had only two small areas around the selected points for calculation the ground plane, which provided good results, even for a floor without any unevenness. After a small modification (also considered in the description of the approach) in the algorithm, which selects the point for estimate the ground plane, we had a vertical ground line which only matched in the lower third of the depth picture. Figure 3 shows that in the upper two thirds the difference between the calculated ground and the real ground was too big to detect any relevant barriers. After that failure we tried to solve this problem in our approach or setup. The First step was to verify the measurements, therefore we subtracted the mean value of the even ground from the mean values of the modified ground. After these results showed acceptable results for the detection of barriers from 5mm up to 25mm, we searched for further reasons. The next test was the linearity of the sensor over the distance. If it has a linear characteristic for the depth sensor, then our approach should work in general. Therefore, we made different measurements from an even surface, a 5 mm and 10 mm barrier in a distance of 40 cm. The result in Figure 3 shows the ground and the calculated virtual ground and a 5mm doorstep obstacle. This shows that the sensor has not a perfect linear characteristic; so, it is difficult to calculate a virtual ground which is represented by a plain or line and use it for a simply background subtraction. The difference between the calculated ground and the real ground is bigger than the standard deviation, which means that we would detect false positive barriers. Also, the difference to the 5 mm footstep is only few mm above the standard deviation and in comparison to the error between real ground to calculated ground, it seems to be difficult to detected obstacles below 10 mm, but for the HE Assessment we need a resolution up to 3 – 4 mm. On the other hand, Figure 3 shows a good difference level between ground and 5 mm barrier, which points out that the choice of the points to calculate the virtual ground plane has a big influence on the further results. So, it is difficult to find a selection algorithm such that the correct points are chosen to get optimal result by minimal calculation cost.

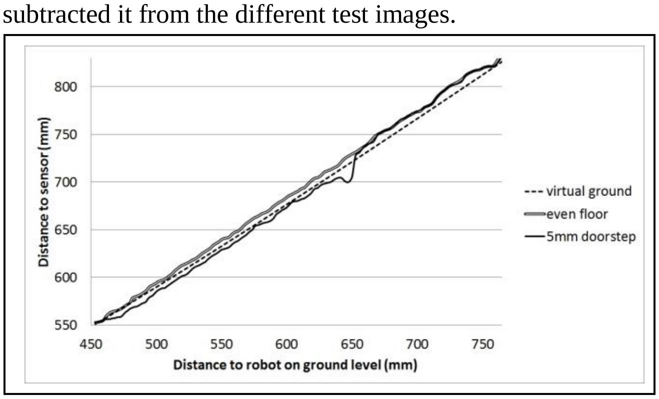

Figure 3. Visualisation of the calculated ground (dotted line) and the measurement from the ground (double line) and the 5 mm doorstep (single line).

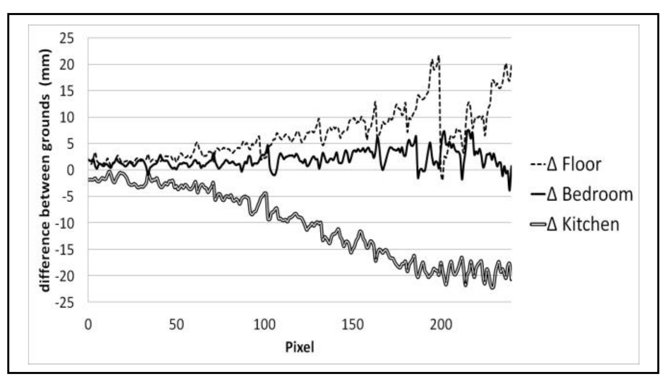

Figure 4. Visualisation of dependency of different floorings in comparison to the general mean ground value. One vertical row is plotted as reference

B. Sensor independence related to the surface

Also, the independence of the sensor compared to the flooring was tested, by measuring 4 different floor types. Two different kinds of carpet, PVC coating and laminate and the transition from laminate to carpet were tested. For each surface we made 30 single measurements and computed the mean value over all 30 single frames on pixel base. Then, we used these mean values to calculate the overall mean value for the ground. From each measurement we selected the mean values of middle column and subtracted it from the corresponding value of the overall mean depth picture. The results are shown in Figure 4 and lead us to the fact, that the different floorings have an influence on the distance values and the reliability of the sensor. As you can see on Figure 4, only the differences in the first 50 pixel, which are equivalent to a distance of 40cm to 55 cm in front of the sensor, are between the first standard deviation (about 6mm). This measurement represents a distance to the sensor between approx. 20cm to 84 cm. This result pointed out that it is advisable to calibrate the sensor for each subsurface and every day to reduce the errors during the measurement or use another model of this sensor type, e.g., the Primesense Carmine 1.09 with higher depth resolution or a complete other type of sensor to detect the unevenness of the floor.

C. Gait parameters vs. floorings

Parallel to the test for the detection of unevenness of the floor we made first measurements in a domestic environment with 5 users (two females/ three males) in the age between 42 – 76 years for a first validation of our approach to calculate gait speed, stride and step length and, when possible, to see differences between different floorings by using the Microsoft Kinect and the openNI tracker. For all measurements the Turtlebot 2 stands at a predefined position, similar to final setup when the mobile robot drives to different OOL's for measurement. Each subject has to walk 5 times in direction to the mobile robot for the same conditions. Each test person has to fulfil a test with 10 different conditions. Two different coatings (carpet / parquet), three different doorsteps (5mm, 10mm and 25 mm height) and each condition under dark and normal lighted condition. So we get a data base of 250 measurements over all conditions and subjects. The first results for the step-, stride length and self-selected gait speed (SGS) on parquet, high pile carpet and different doorsteps are presented. As you can see in Figure 5 and Figure 6 a difference between the stride length and the SGS could not be only detected for elderly persons, also for mid-aged persons, depending on the floorings. Also, it seems like as if the variation of the step- and stride length depends on the coatings. But further tests with more measurements, longer walking distances and time periods must be evaluated to verify our first results. Nevertheless evidence that the floorings have an impact on the gait analysis in the domestic environment was shown. Without the knowledge of the characteristic of the flooring, e.g., like the most classical automated approaches it could lead to false decisions related to the decreasing of the SGS on some coatings. These give first evidence that the quality of balance and gait analysis depended also on the floorings. Further tests must be made to get reliable facts, what kind of obstacles has an influence and how big is the impact.

VI. CONCLUSION

A new approach for the detection of fall relevant unevenness and a first idea of an advanced gait analysis which used this information for better results in the context of an automated Housing Enabling assessment was presented. Therefore, we used a mobile robot platform the Turtelbot 2. As depth sensor a Primesense Carmine 1.08 is used for the detection of unevenness with the original OpenNI driver v.2.1.0 and a Microsoft Kinect with the ROS openNI tracker Node for the balance and gait analysis. The Carmine sensor was mounted up-side down below the third level of the Turtelbot platform in a height of approx. 34 cm. The Kinect was mounted on the highest level (height approx. 55cm). We were able to determine the position and orientation of the sensor, only from a small knowledgebase. Our approach is aimed at calculate a virtual ground, which is the reference for barriers, because in a normal scenario it is unrealistic to have the chance to make a clean depth picture from each part of the room without any carpets on the subsurface or other stumping blocks. But, our measurements have shown that the combination of our approach with this sensor, the mounting and the needed resolution does not work in a proper way. This depends on tree facts.

- First point is the depth resolution of the sensor. The noise of the sensor is near to the values that we want to detect.
- Second point is the instability of the sensor, depending on different factors, is too big. As we can show, the floorings and the gloss of it have a big influence on the depth values. The difference is sometimes even more than the third standard deviation.
- Third point is the quality of our algorithm to select the points for the calculation of the virtual ground. We should add a validation step if the virtual ground matched with the most points. Otherwise we should select new points or to change to a spline based approach.

Finally, we could say that the Primesense Carmine 1.08 Sensor has some advantages, like the price and the relatively good resolution and a low noise in fact of the price and range. But, the quality is not high enough for this application in the frame of the housing enabling Assessment or to determine relevant unevenness of the floor.

Our second approach to use the additional information about the floorings to raise the quality of gait analysis in the domestic environments seems to be essential to generate reliable data. For the first results we could show that an influence of the flooring exists, but for final statements we have to evaluate this approach with more users and with more flooring and other important facts. The first results allow the statement that all automated gait analysis in unsupervised environments should consider the texture and unevenness of the flooring.

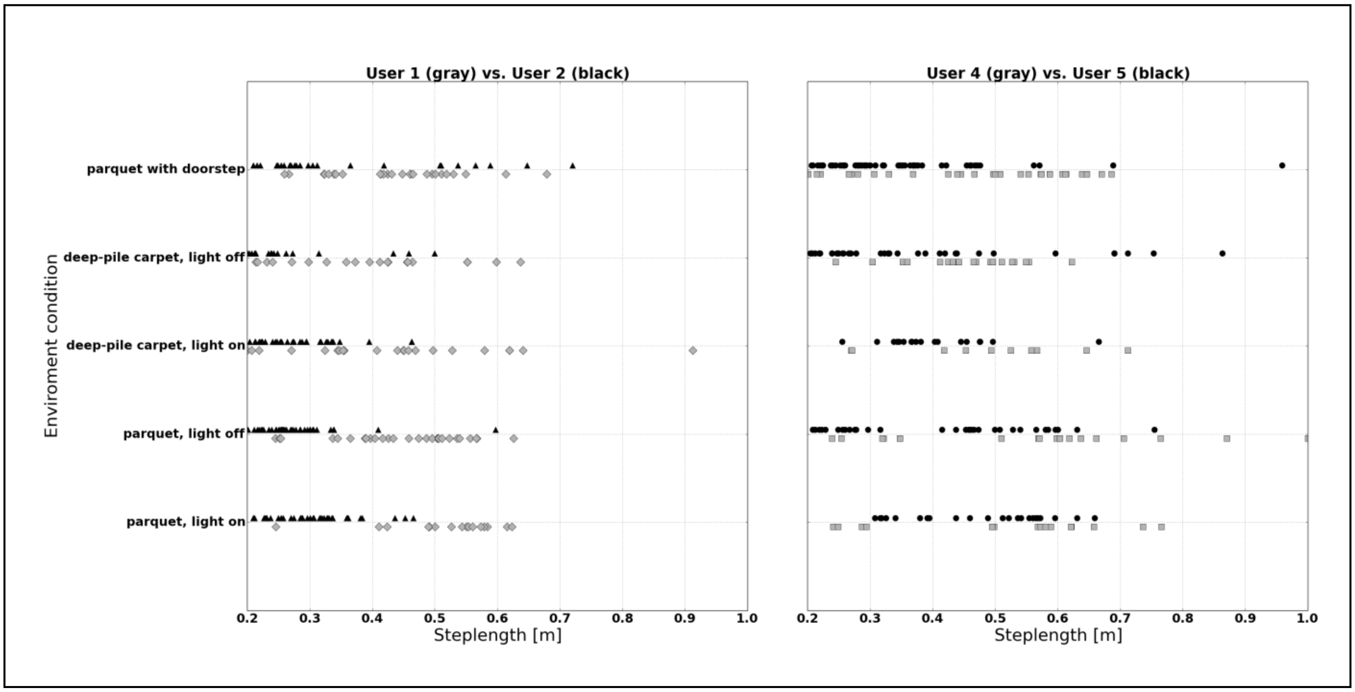

Figure 5. Influence of floor conditions to the step-length of different subjects (grey: mid-age, black: elderly). Left side: two female subjects and on the right site two male subjects.

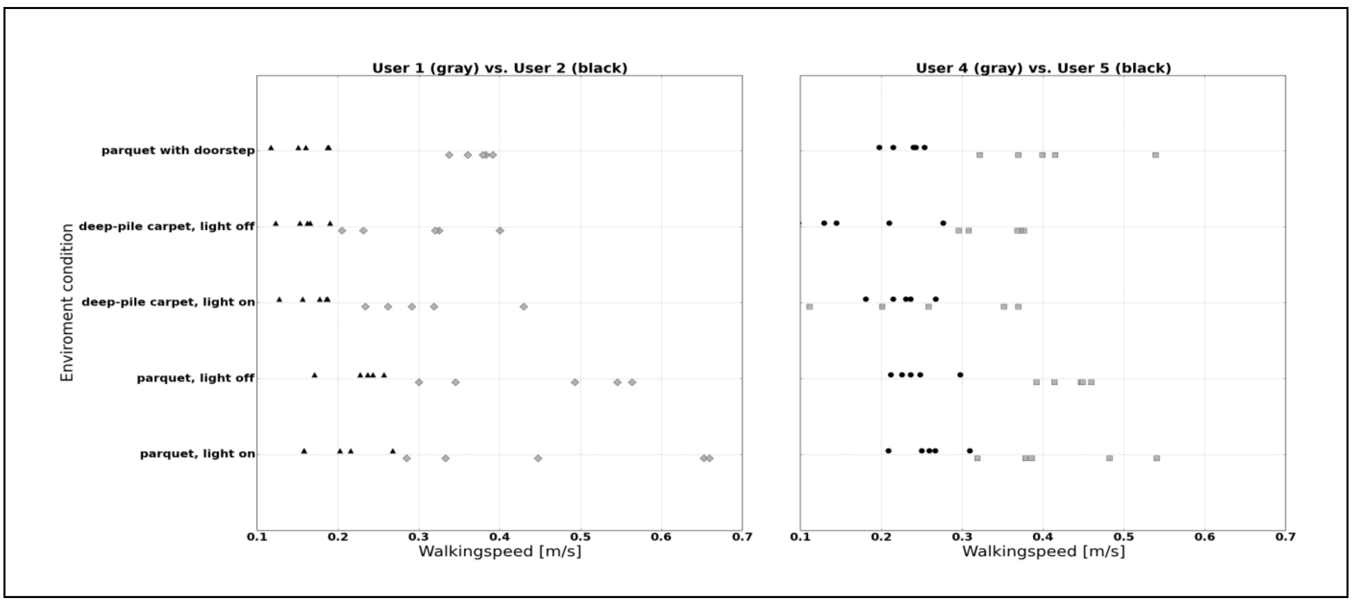

Figure 6. Influence of floor conditions to the gait speed of different subjects (grey: mid-age, black: elderly). Left side: two female subjects; Right site: two male subjects.

REFERENCES

[1] K. Böhle, K. Bopp, and M. Dietrich, “The "Artificial Companion" - a useful guiding principle for development and implementation of technical assistance systems in care arrangements?,” In Proceedings of: 6. Deutscher AAL-Kongress: "Lebensqualität im Wandel von Demografie und Technik", Berlin, VDE 2013.

[2] J. Meyer, M. Brell, A. Hein, and S. Gessler; “Personal Assistive Robots for AAL Services at Home - The Florence Point of View,” 3rd. IoPTS workshop, Brussels, 2009.

[3] T. Frenken, M. Isken, N. Volkening, M. Brell, and A, Hein, “Criteria for Quality and Safety while Performing Unobtrusive Domestic Mobility Assessments Using Mobile Service Robots,” Ambient Assisted Living, Advanced Technologies and Societal Change 2012, VDE, 2012, pp. 61-76.

[4] T. Rehrl et al., “The Ambient Adaptable Living Assistant is Meeting its Users,” AAL Forum 2012.

[5] F. J. Imms and O. G. Edholm, “Studies of gait and mobility in the elderly”, Age Ageing, vol. 10, no. 3, Aug. 1981, pp. 147–156.

[6] M. Montero-Odasso et al., “Gait velocity as a single predictor of adverse events in healthy seniors aged 75 years and older,” J Gerontol A Biol Sci Med Sci, vol. 60, no. 10, Oct. 2005, pp. 1304–1309.

[7] N. Volkening, A. Hein, M. Isken, T. Frenken and M. Brell, “Housing Enabling – Detection of imminent risk areas in domestic environments using mobile service robots,” 6. Deutscher Kongress Ambient Assisted Living at Berlin, Germany, VDE Verlag 2013, pp. 479-485.

[8] D. J. Cook and S. K. Das, “How smart are our environments? An updated look at the state of the art,” Pervasive and Mobile Computing, vol. 3, no. 2, 2007, pp. 53 – 73.

[9] S. B. Thies, J. K. Richardson, and J. A. Ashton-Miller, “Effects of surface irregularity and lighting on step variability during gait: A study in healthy young and older women,” Gait & Posture, vol. 22, iss. Aug. 1, 2005, pp. 26-31, ISSN 0966-6362.

[10] D. S. Marigold and A. E. Patla, “Age-related changes in gait for multi-surface terrain”, Gait&Posture, vol. 27, iss. 4, May, 2008, pp. 689-696.

[11] Primesense – 3D Carmine 1.09 Sensor, Product Information, Available Online: http://i3du.gr/pdf/primesense.pdf, last access: June 27, 2014.

[12] Professional association rules for safety and health at work, BGR 110, 04-2007, Federation of Trade Associations, Online: http://publikationen.dguv.de/dguv/pdf/10002/bgr-110.pdf, last access: June 26, 2014.

[13] C. N. Scanaill et al., “A review of approaches to mobility telemonitoring of the elderly in their living environment,” Ann Biomed Eng, vol. 34, no. 4, Apr., 2006, pp. 547–563.

[14] K. Cameron, K. Hughes, and K. Doughty, “Reducing fall incidence in community elders by telecare using predictive systems,” in Proc. 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 3, 1997, pp. 1036–1039.

[15] J. A. Kaye et al., “Intelligent Systems For Assessing Aging Changes: home-based, unobtrusive, and continuous assessment of aging,” The journals of gerontology. Series B, Psychological sciences and social sciences, vol. 66, iss. 1, July 1., 2011, pp. i180–i190, doi: 10.1093/geronb/gbq095.

[16] T. Frenken et al., “A novel ICT approach to the assessment of mobility in diverse healht care enviroment,” CEWIT-TZI-acatech Workshop "ICT meets Medicine and Health" (ICTMH 2013), April, 2013.

[17] M. P. Poland, D. Gueldenring, C. D. Nugent, H. Wang, and L. Chen, “Spatiotemporal Data Acquisition Modalities for Smart Home Inhabitant Movement Behavioural Analysis,” ICOST '09, Proceedings of the 7th International Conference on Smart Homes and Health Telematics, Springer, 2009, pp. 294-298.

[18] E. E. Stone and M. Skubic, “Passive In-Home Measurement of Stride-to-Stride Gait Variability Comparing Vision and Kinect Sensing,” 33rd Annual International Conference of the IEEE EMBS, Boston, Massachusetts, USA, 2011, pp. 6491-4.

[19] M. Gabel, R. Gilad-Bachrach, E. Renshaw, and A. Schuster, “Full Body Gait Analysis with Kinect,” 34th Annual International Conference of the IEEE EMBS, San Diego, USA, 2012.

[20] A. Petrovskaya and A. Y. Ng, “Probabilistic mobile manipulation in dynamic environments, with application to opening doors,” in International Joint Conference on Artificial Intelligence (IJCAI), 2007, pp. 2178-2184.

[21] C. L. Breazeal, “Sociable machines: Expressive social exchange between humans and robots,” Ph.D. dissertation, Massachusetts Institute of Technology, Department of Electrical Engineering and Computer Science, 2000.

[22] C. Ray, F. Mondada, and R. Siegwart, “What do people expect from robots?,” in IEEE/RSJ International Conference on Intelligent Robots and Systems, 2008, pp. 3816–3821.

[23] M. Isken et al., “Enhancing Mobile Robots’ Navigation through Mobility Assessments in Domestic Environments,” in Proceedings 4. Deutscher Kongress, Ambient Assisted Living, VDE Verlag, 2011, pp. 223-238.

[24] M. Brell, J. Meyer, T. Frenken, and A. Hein, “A Mobile Robot for Self-selected Gait Velocity Assessments in Assistive Environments,” in The 3rd International Conference on Pervasive Technologies Related to Assistive Environments (PETRA’10), Samos, Greece, June 2010, ISBN 978-1-4503-0071-1.

[25] G. Carlsson, B. Slaug, A. Johannisson, A. Fänge, and S. Iwarsson,. “The Housing Enabler - Integration of a computerised tool in occupational therapy undergraduate teaching,” CAL Laborate, June, 2004, pp. 5 – 9,

[26] T. Helle et al., “The Nordic Housing Enabler: Interrater reliability in cross-Nordic occupational therapy practice,” Scandinavian Journal of Occupational Therapy, Dec. 17, 2010, pp. 258-66.

[27] A. Fänge, “Strategies for evaluation of housing adaptations – Accessibility, usability and ADL dependence”, ISBN91-974281-5-9. Doktorsavhandling. Institutionen för klinisk neurovetenskap, Lunds Universitet. Lund, Sverige, 2004.

[28] M. Cesari et al, “Prognostic Value of Usual Gait Speed in Well-Functioning Older People—Results from the Health, Aging and Body Composition Study”, Journal of the American Geriatrics Society, vol. 53, 2005, pp. 1675–1680.

[29] P. Udsatid, N. Niparnan, and A. Sudsang, “Human Position Tracking for Side By Side Walking Mobile Robot using Foot Positions,” Proceedings of the 2012 IEEE International Conference on Robotics and Biomimetics, Dec. 11-14, 2012, pp. 1374 - 1378 Guangzhou, China.

[30] E. E. Stone and M. Skubic, “Unobtrusive, Continuous, In-Home Gait Measurement Using the Microsoft Kinect,” IEEE Transactions on biomedical engineering, vol. 60, no. 10, Oct. 2013, pp. 2925-32.

[31] T. Pallej, M. Teixid, M. Tresanchez, and J. Palacn, “Measuring Gait Using a Ground Laser Range Sensor,” Sensors, vol. 9, no. 11, 2009, pp. 9133–9146.

[32] Zhengyou Zhang, "Microsoft Kinect Sensor and Its Effect," IEEE Multimedia, vol. 19, no. 2, pp. 4-10, April-June 2012, doi:10.1109/MMUL.2012.24